

# CoSMoEs: Compact Sparse Mixture of Experts

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Sparse Mixture of Expert (MoE) models are popular foundational architectures at large scale, however, under-explored at smaller sizes. Here, we show how to enable Compact Sparse Mixture of Experts (CoSMoEs) for on-device inference. Specifically, we tackle the three main on-device dimensions: Quality, Memory and Latency. Along the quality axis, we show that in a fair evaluation (removing confounding factors) MoE architectures outperform FLOP-aligned dense models at on-device scale. We introduce weight-decomposed experts, further improving the MoE model performance. Regarding model memory and latency, we significantly improve model offloading efficiency and, in turn, reduce model inference latency.

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**Code:** Model code and checkpoints will be released soon!



## 1 Introduction

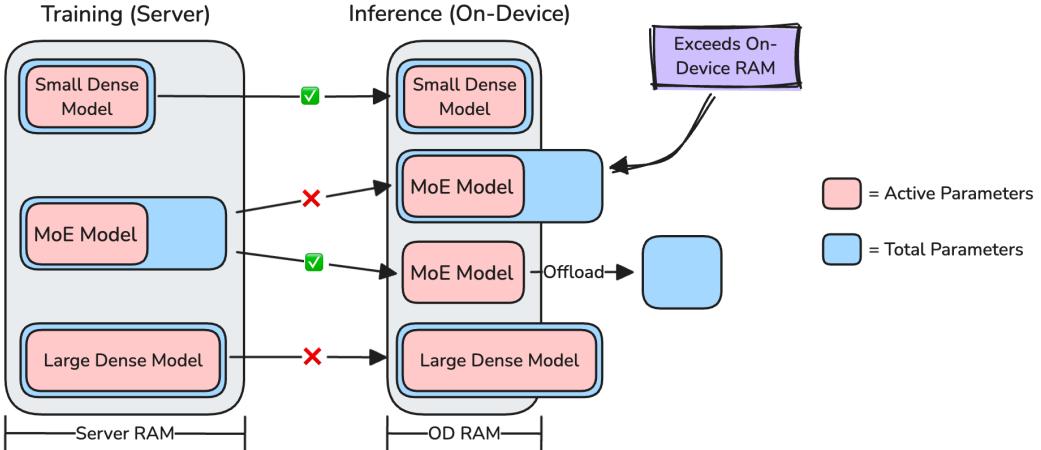
Mixture of Experts (short: MoEs) have been a popular extension of the transformer architecture [Vaswani et al. \(2023\)](#), introducing the idea that each token of the input sequence is not fed through a single, dense network per layer, but a set of sub-networks, or “experts”. To allow every input token to utilize a mixture of expert, the sub-networks are usually combined with a gating mechanism, which determines the contribution of each expert.

In the general MoE setting, going back to [Jacobs et al. \(1991\)](#) and [Jordan and Jacobs \(1993\)](#), all experts are used to compute the final layer output. Building on top of this general architecture, sparse Mixture of Expert models have been proposed as a more compute-efficient alternative, only allowing a subset of experts to be activated for each token [Cai et al. \(2024\)](#). Recently, many foundational models have adopted the MoE approach, such as [Qwen Bai et al. \(2023\)](#); [Yang et al. \(2024\)](#), OLMoE [Muennighoff et al. \(2024\)](#), Mixtral [Jiang et al. \(2024\)](#), Deepseek [\(2024\)](#), *inter alia*.

In comparison to large-scale foundational Mixture of Expert models, optimized for highly parallelized server-side inference, in this work, we focus on small-scale foundational MoEs models deployed on edge devices<sup>1</sup>. As such, this comes with a set of challenges around single-sample, on-device inference, which can be classified into three categories: Quality, Memory and Latency.

**Quality:** We tackle the fundamental research question if Mixture-of-Expert models can improve language modeling abilities over dense models at on-device scale. In comparison to previous work (e.g. [Jiang et al. \(2024\)](#)), we set up a truly fair comparison between MoEs and dense models. Here, we define a “fair comparison” of an MoE model against its dense counterpart by aligning for both, the same number of active parameters (i.e. FLOP aligned, short: FA) and total parameters (i.e. parameter aligned, short: PA). We further assume that a “fair comparison” between models should reduce confounding factors. Along those lines, we normalize models for training datasets, recipes, and architectures wherever possible. This way, we can make a clear performance attribution to the MoE component in isolation. In our evaluation, we show that MoE-style architectures improve the average language modeling performance by at least 2.35% absolute across on-device model sizes. Based on these results, we propose a novel MoE model extension following the core intuition of “expert specialization”. Using weight-decomposed experts, we show up to an additional 1.1% language modeling improvements.

<sup>1</sup>We focus on two model sizes: “Wearables-sized” models at 200M active parameters and “Phone-sized” models at 1.4B active parameters.



**Figure 1** Server-side training environment (left) compared to the memory-constraint inference environment (right), showing deployment restrictions for parameter heavy MoEs and large dense models on edge devices.

*Memory/Latency:* For server-side models, language modeling ability presents the main dimension for model improvements. In the on-device context, however, we face two additional hard constraints: Memory and latency. As depicted in Figure 1, models trained in server environments, with loose memory and latency restrictions, face additional constraints for inference on edge-devices. While these restrictions are architecture independent, MoE-style models with a high total parameter count are more impacted. Luckily, the sparsity property of MoE architectures allows to circumvent this restriction by offloading unused experts, effectively reducing the model size in memory to the active parameter count (see Figure 1). Reducing the model memory through expert offloading, however, comes at the cost of 4-20x increased inference latency, since experts might need to be offloaded for every single token in the output sequence Xue et al. (2024). To relax this memory/latency trade-off, we propose a novel “block-wise expert selection” loss, reducing expert offloads by 6x and, in turn, improving inference latency by 50% compared to default offloaded MoEs.

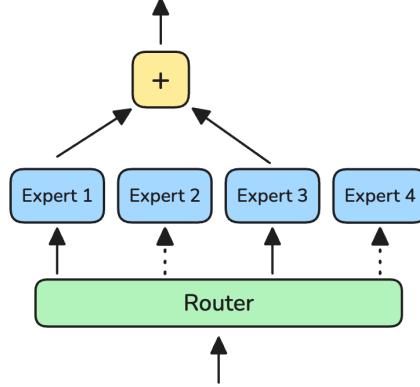
## 2 CoSMoEs Models

### 2.1 Sparse Mixture-of-Experts

At the core of this work is the sparse Mixture-of-Expert (MoE) architecture, popularized by works such as GShard Lepikhin et al. (2020) and Switch Transformers Fedus et al. (2022). While MoEs can generally be implemented for different parts of the architecture, the most common approach is to replace the single dense feed-forward layer with a router component and multiple experts (see Figure 2). Selecting a discrete subset of experts at each step, sparse MoE models can be defined by their active parameters (FLOPs) and total parameters (model size in memory). The resulting FLOP-to-parameter ratio directly translates to increased training and inference efficiency, without sacrificing model performance. To find a suitable subset of experts, different expert routing paradigms have been established, either selecting experts per token (token choice or “TC”) Shazeer et al. (2017) or per expert (expert choice or “EC”) Zhou et al. (2022). Here, we use the token choice expert routing paradigm (illustrated in Figure 2) following the findings in OLMoE Muennighoff et al. (2024), showing that EC does not bring clear improvements for text-only models. Please note that from here on out, we will refer to sparse MoEs as solely “MoEs” for brevity. However, all evaluated models in this paper are sparse versions of Mixture-of-Expert models.

### 2.2 Weight-Decomposed Experts

To reduce the naturally large total parameter count of MoE-style models, we propose a lightweight definition of experts using matrix weight decompositions (“WD”) similar in spirit to Low Ranking (“LoRa”) adapters Hu et al. (2021). Intuitively, individual experts are intended to “specialize” towards a subset of, ideally,  $\frac{1}{\#Experts}$  tokens. Based on this intuition, we replace expert matrices of shape  $n \times m$  with weight decompositions of shape  $n \times r$  and  $r \times m$  as shown in



**Figure 2** Sparse Mixture-of-Experts architecture with Token Choice (TC) Routing and  $k=2$

Figure 3 and defined in Equation 1:

$$M_{n \times m} \approx L_{n \times r} \times R_{r \times m} \quad (1)$$

Here, the original matrix  $M$  is replaced by  $L$  and  $R$ , with  $r \ll n$  and  $r \ll m$ . In preliminary experiments, we test multiple reduction factors for  $r$  and find that a decomposition of half the hidden dimension results in the best trade-off between parameter reduction and model performance. Weight decomposed models are from here on out prefix with a *WD* term. To ensure a parameter-aligned comparison, we adjust the number of heads and layers as further elaborated on in section 3.1.

### 2.3 Block-wise Expert Selection

We now explore the second restrictive dimension of MoEs for on-device use cases: Memory and Latency. Multiple lines of research have previously explored inference-time optimizations using predictive expert offloading and bitwidth adaptations, such as EdgeMoE [Yi et al. \(2023\)](#), Mixtral [Eliseev and Mazur \(2023\)](#) and DeepSpeed [Aminabadi et al. \(2022\)](#). Here we explore the expert offloading problem from a new vantage point, proposing a “Block-wise Expert Selection” (BIES) training loss term to reduce the number of expert replacements. Our BIES loss is thereby closely related to the expert load balancing loss proposed in [Fedus et al. \(2022\)](#):

Let  $R$  be a router logits tensor with shape  $(B, T, E)$ . With  $B$  as the batch-dimension,  $T$  as the sequence length and  $E$  as the expert dimension. We compute the routing weights  $W$  by applying the softmax function to  $R$ , scaled by a temperature parameter  $\tau$  as:

$$W = \text{softmax}(\tau R) \quad (2)$$

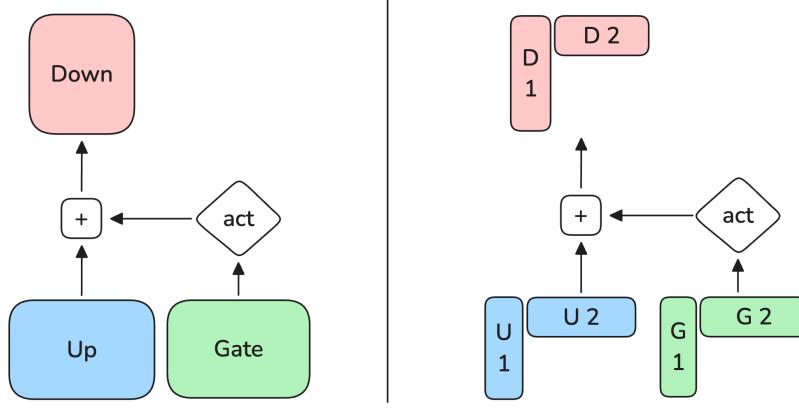
In the non-differentiable part of the loss, we select the top- $k$  experts  $K$  for each token based on the routing weights  $W$ . Let  $S$  be the selected experts tensor with shape  $(B, T, K)$  following

$$S = \text{top\_k}(W, K) \quad (3)$$

We then compute the number of hard expert replacements  $H$  by comparing consecutive tokens’ expert assignments as:

$$\begin{aligned} H_e &= \sum_{b=1}^B \sum_{t=1}^{T-1} |(S_{[b,t+1]} == e) - (S_{[b,t]} == e)| \\ H &= \sum_{e=1}^E H_e \end{aligned} \quad (4)$$

where  $e$  is the expert index and  $S_{[b,t]} == e$  is 1 if expert  $e$  is one of the top- $k$  candidates for token  $t$ . This approach counts every expert replacement twice ( $1 \rightarrow 0$  for the active expert and  $0 \rightarrow 1$  for newly active expert). As a result, we



**Figure 3** Feed Forward Layer: Standard (left) and Weight-Decomposed (right).

divide  $H$  by two and normalize by the batch-size, top-k and number of tokens as follows:

$$H_{norm} = \frac{\lfloor \frac{H}{2} \rfloor}{B \cdot K \cdot (T - 1)} \quad (5)$$

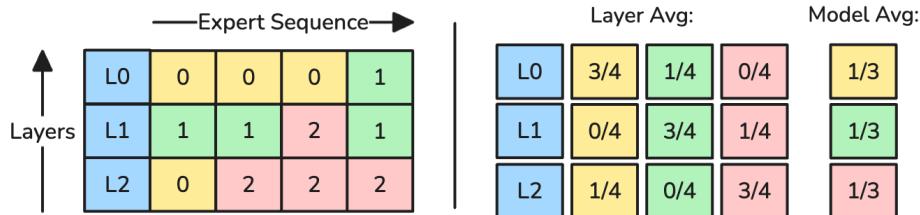
To keep the overall loss term differentiable, we compute a soft expert selection  $L$  by combining the per-expert probability differences between consecutive tokens along the token dimension  $T$ . With  $L_{norm}$  as the normalized soft expert selection, we compute:

$$\begin{aligned} L &= \sum_{b=1}^B \sum_{t=1}^{T-1} \sum_{e=1}^E |W_{b,t+1,e} - W_{b,t,e}| \\ L_{norm} &= \frac{L}{B \cdot T} \end{aligned} \quad (6)$$

The final loss is defined as product of the hard and the soft expert selection loss.

$$loss = H_{norm} \cdot L_{norm} \quad (7)$$

As described above, the block-wise expert selection loss is defined on sequence level. We adjust the standard load balancing loss [Fedus et al. \(2022\)](#) to also operate on sequence level (following [Lin et al. \(2024\)](#)) to avoid loss inconsistencies, allowing the model to “cheat”. For example, using 2 experts and 2 layers, the loss function can be exploited by consistently selecting expert 0 in layer 0 and expert 1 in layer 1, hence having a perfect 50:50 load balancing loss at the model level, as well as a minimal BIES on sequence level. See Figure 4 for a visualization of this example using 3 layers and 3 experts.



**Figure 4** Example expert selection (for simplicity,  $k=1$ ) for individual layers and the complete model.

### 3 Evaluation

#### 3.1 Model Setup and Training Recipes

We compare two on-device sizes: “Phone-sized” ( $\sim 1\text{-}3\text{B}$  parameters) and “Wearable-sized” ( $\sim 100\text{-}300\text{M}$  parameters) as well as three architectures: Dense, MoE and WD MoE, all presented in Table 1. We further train the standard MoE architecture with our novel “Block-wise Expert Selection” (BIES) loss<sup>2</sup>. All models are based on the Llama3 architecture, with the additional MoE component consisting of eight total experts, with two active for every token. We follow standard approaches provided in the Huggingface codebase for the expert implementation [Wolf et al. \(2020\)](#). We keep model all hyper-parameters as constant as possible while aligning dense and MoE models along the active and total parameter counts. When in doubt, we follow the findings in [Liu et al. \(2024\)](#) and select depth over breadth.

Model	Params	L	H	Hid	Seq	Steps	Bsz
<b>Phone-sized models, <math>\sim 1\text{B}\text{-}3\text{B}</math> Parameters</b>							
Dense	1.50B	16	32	2048	2048	310k	2048
MoE	1.37B (3.75B)	24	18	1440	2048	310k	2048
+ WD	1.42B (3.65B)	26	20	1600	2048	310k	2048
Dense	3.61B	28	24	3072	2048	310k	2048
<b>Wearable-sized models, <math>\sim 100\text{-}200\text{M}</math> Parameters</b>							
Dense	189M	19	8	512	2048	310k	2048
MoE	188M (377M)	19	8	432	2048	310k	2048
+ WD	188M (377M)	32	10	400	2048	310k	2048
Dense	380M	29	12	768	2048	310k	2048

**Table 1** On-device model candidates. Params = #Active (#Total) Parameters, L = Layers, H = Self-Attention Heads, Hid = Hidden size, Seq = Sequence length, Bsz = effective batch-size

#### 3.2 Training Datasets

To pre-train all models using the FineWeb Education dataset (FW-edu, [Penedo et al. \(2024\)](#)), a 1.4 trillion token text dataset provided by Huggingface [Wolf et al. \(2020\)](#). Compared to other popular, open-source pre-training datasets, such as RedPajamas [Computer \(2023\)](#); [Weber et al. \(2024\)](#), FW-edu represents a smaller scale, yet high-quality, general purpose language dataset, filtered with Llama-70B educational prompts.

#### 3.3 Metrics and Benchmarks

To evaluate the **language modeling performance** we use the public EleutherAI LM eval harness and nine language modeling evaluations [Gao et al. \(2024\)](#), namely, MMLU, AGI-English, Arc-challenge and -easy, BoolQ, PIQA, SIQA, HellaSwag and WinoGrande. We pick this subset in accordance with Llama3 [Grattafiori et al. \(2024\)](#) and MobileLLM [Liu et al. \(2024\)](#) evaluations. We exclude long-context evaluations (e.g. SQuAD, DROP, QuAC), due to our sequence length restriction of 2048. To evaluate our **Block-wise Expert Selection (BIES)** loss, we show two offloading-specific metrics: The Expert Replacement Ratio (ExRep) and optimal expert balance. Specifically, the Expert Replacement is defined along the lines of equations 4 and 5, calculating the percentage of realized replacements. Regarding the optimal expert balance, we calculate the average per-layer delta between the uniform distribution and the realized expert balance. Lastly, to investigate the model candidates’ **memory and latency performance**, we show the per-token model latency (i.e. the realized generation speed) and peak memory.

### 3.4 Results

#### 3.4.1 Language Modeling Performance

Our results on the language modeling task are presented in Table 2. We show a random baseline in the top row of the table, followed by the main model comparisons. The MoE-based results are framed by two rows of dense model candidates. On top of each sub-table, we show the FLOP aligned model (short: FA), at the bottom we present the

<sup>2</sup>The BIES model uses the standard MoE model architecture and is not separately mentioned in Table 1.

Model	Params	MMLU	AGI-E	Arc-C	Arc-E	BoolQ	PIQA	SIQA	HellaS	OBQA	WinoG	Avg
<b>Random Baseline</b>												
Random	-	24.53	16.07	21.08	25.25	51.07	51.74	33.11	26.31	29.40	50.83	32.94
<b>Phone-sized models, ~1B-3B Parameters</b>												
Dense	1.50B	24.78	17.99	36.95	74.03	59.08	74.54	41.76	59.88	41.20	57.54	48.78
MoE	1.37B (3.75B)	<b>25.96</b>	17.65	42.58	76.77	60.89	75.52	42.12	65.07	42.40	<b>62.35</b>	51.13
+ BIES	1.37B (3.75B)	25.40	17.50	41.55	<u>77.02</u>	62.81	76.06	41.91	63.14	42.60	59.04	50.70
+ WD	1.42B (3.65B)	23.90	<b>18.20</b>	<u>43.69</u>	76.81	<b>66.76</b>	<u>76.39</u>	<b>45.14</b>	<u>66.51</u>	<u>42.80</u>	62.04	<b>52.22</b>
Dense	3.61B	<b>26.41</b>	16.82	<b>44.54</b>	<b>77.9</b>	65.87	<b>77.48</b>	43.3	<b>67.18</b>	<b>45.00</b>	<b>63.46</b>	<b>52.80</b>
<b>Wearable-sized models, ~100-200M Parameters</b>												
Dense	189M	22.9	16.82	23.29	56.82	57.09	64.15	37.82	36.36	32.8	50.99	39.90
MoE	188M (377M)	<b>25.27</b>	17.37	27.9	<u>63.09</u>	58.39	69.04	39.61	44.09	<b>34.4</b>	53.03	43.22
+ BIES	188M (377M)	24.27	<u>17.58</u>	24.83	58.84	<b>59.82</b>	66.49	38.64	39.70	33.40	49.96	41.35
+ WD	188M (377M)	23.64	17.16	<u>28.58</u>	62.58	57.13	<b>69.31</b>	<b>40.28</b>	<u>46.15</u>	33.20	<b>54.38</b>	<b>43.24</b>
Dense	380M	24.79	<b>17.86</b>	<b>28.92</b>	<b>64.35</b>	52.02	69.21	39.97	<b>46.53</b>	33.80	51.62	42.91
<b>Public Baselines across Model Sizes</b>												
MobLLM (2024)	135M	23.02	17.45	19.97	46.38	60.34	64.96	38.08	38.17	28.40	52.57	38.93
MobLLM (2024)	350M	26.33	17.47	23.89	56.4	61.96	68.88	39.87	49.57	31.00	57.38	43.28
Llama3.2 (2024)	1.4B	36.92	18.80	31.31	65.40	63.61	74.54	42.84	47.74	26.20	60.06	46.70
Llama3.2 (2024)	3.6B	54.01	22.53	42.32	74.41	72.81	76.71	47.13	55.32	31.20	69.30	54.50
OLMoE (2024)	1.68B (6.92B)	25.74	17.19	40.87	74.20	60.52	74.70	44.37	60.38	38.40	58.72	49.50

**Table 2** Model comparison on zero shot LM evaluations. Params = #Active (#Total) Parameters, BIES = Block-wise Expert Selection, WD = Weight-Decomposed, MobLLM = MobileLLM. Public baselines are evaluated using the EleutherAI LM eval harness (2024).

parameter aligned (short: *PA*) dense model. For the MoE candidates, we show the standard MoE followed by the BIES and weight decomposed (WD) versions. In the bottom sub-table we show additional models from the literature to put our results into context<sup>3</sup>.

*Phone-sized models:* We show that all MoE model candidates outperform the random baseline by a large margin and consistently improve over the FA dense model by at least 2%. Comparing individual tasks, we find that for MMLU and AGI-English, all tested models only provide minor gains compared to the random baseline, showing clear potential for further improvements in this area. Regarding all other evaluation tasks, clear improvements are observed. Between MoE models, the weight-decomposed model performs best overall, while for individual metrics the top-performing candidate varies. We also find a minor performance regression when using the block-wise expert selection loss. Compared to the PA dense model, MoE candidates perform better in 3 out of 10 metrics, falling only about half a percent short on average. Putting our observed model performances into the context of previously published models (1B and 3B Llama3.2, OLMoE 1B-7B), we find that the MoE model candidates outperform the FA Llama 3.2 1B and OLMoE models, however, can not reach the PA Llama 3.2 3B performance. We believe that this clearly shows that our MoE-style models are competitive to top open source candidates.

*Wearable-sized models:* The wearable-sized evaluation shows generally similar trends. All MoE candidates outperform the random baseline and FA dense model. MMLU and AGI-English results are insignificantly above the random baseline, while all other tasks show meaningful improvements. The weight-decomposed model achieves the best MoE performance, this time even outperforming the PA dense model. At wearable-scale, at least one of the MoE models outperforms the PA dense model in 6 of 10 tasks. Looking at the comparison to the previously published MobileLLM model, we see improvements at the 125M and 350M parameter scale. Again, the BIES model shows a slight performance drop compared to the standard MoE setup.

Model	ExRep (↓)	Tok/s Gen (↑)	ΔUni (↓)
MoE	43.82	15.02	<b>9.60</b>
+ BIES	<b>6.55</b>	<b>23.10</b>	9.67

**Table 3** Impact of the BIES Loss on Expert Replacement (in percent), generation speed (token/second), and diversion from the uniform expert distribution (in percent) ↓ = lower is better, ↑ = higher is better.

<sup>3</sup>Previously published models are also evaluated using the EleutherAI LM eval harness, but not aligned for confounding factors and, hence, not directly comparable.

### 3.4.2 Offload Efficiency

As previously shown in Figure 1, executing MoE models on-device requires offloading experts to stay within memory constraints. This necessity, however, causes significant latency regressions, rooted in the added offloading overhead. Let  $E$  be the set of experts,  $S$  the set of selected experts, and  $N = E \setminus S$  the set of non-selected experts. For each token in the output sequence, the following offloading logic is applied to ensure the number of experts in GPU memory never exceeds the number of active experts:

$$\begin{aligned} & \text{If } S \neq S_{\text{prev}} : \\ & \quad \forall e \in N \rightarrow \text{CPU} \\ & \quad \forall e \in S \rightarrow \text{GPU} \\ & \quad S_{\text{prev}} \leftarrow S \end{aligned} \tag{8}$$

Since the expert selection and, hence, offloading frequency is data-dependent, we use a 100 sample subset of the C4 dataset [Raffel et al. \(2020\)](#) as a proxy for general text data. Table 3 presents the results of this evaluation along three dimensions: The expert replacement percentage (ExRep), the realized inference speed in tokens per second (the full set of on-device benchmarks, putting the generation speeds into context, is presented in section 3.4.3), and the model diversion from the ideal uniform expert balance ( $\Delta\text{Uniform}$ ). Comparing the standard MoE model with our BIES extension, we find that the additional loss term causes a significant reduction in expert replacements, reducing the number of expert switches by over 6 times. This also directly converts into a real-world generation speed improvement of over 1.5x. Looking at the third metrics in Table 3, we observe a minor increase in the optimal expert balancing metric of less than 1% relative<sup>4</sup>.

Besides the quantitative results in Table 3, we show a qualitative example in Figure 5. Compared to the standard MoE model (bottom), the BIES loss extended model (top) effectively reduces the number of expert replacements from 21 → 11, while conserving expert diversity (both models actively use 6 out of the 8 experts).

Furthermore, to get a better understanding of the per-layer impact of the BIES loss, we plot the layer-wise expert balance analysis in Figure 6. We find that when using the blocked expert selection, a larger expert divergence is observed in lower layers, while the standard MoE model shows a generally higher expert balance divergence in higher layers. While we don't have a clear understanding of the reasoning and impact of these differences, we believe that higher expert diversity in later layers seems preferable, given the general intuition that lower layers encode more local, syntactic information, while higher layers represent more global and semantic structures.

### 3.4.3 On-Device Benchmarks

We now evaluate the model candidates along the two main on-device dimensions, namely, latency and peak memory. Given that on-device models are oftentimes executed in either CPU based environments or using proprietary accelerators, we compare model latency in both, CPU and GPU environments<sup>5</sup>. Furthermore, despite a variety of inference-optimizations available across different modeling frameworks and code bases (e.g. EdgeMoE [Yi et al. \(2023\)](#)), this paper targets training-time improvements. As a result, we use standard inference code provided in the Huggingface Transformers library [Wolf et al. \(2020\)](#) and the gpt-fast codebase [PyTorch Labs \(2023\)](#) without further inference optimizations.

Table 4 shows our results along four dimensions: (1) The language modeling performance, as previously shown in Table 2, (2) the model inference speed in tokens per second, measured across 128 tokens in CPU and GPU environments, (3) the model peak memory after 128 token generations in GB of RAM and (4) the suitability of the model for on-device inference (in line with Figure 1).

Besides the previously shown model candidates, we add an additional standard MoE offloading setup following equation 8, indicated as “Off”, besides the “BIES” offloaded model.

*Latency:* Looking at the generation latency, we find that on CPU, the FA dense model achieves the highest token per second generation, MoE model candidates are slightly slower, and the PA dense model regresses the generation speed by 2x. On GPU, MoE models generally produce less tokens per second than dense models, mainly caused by the

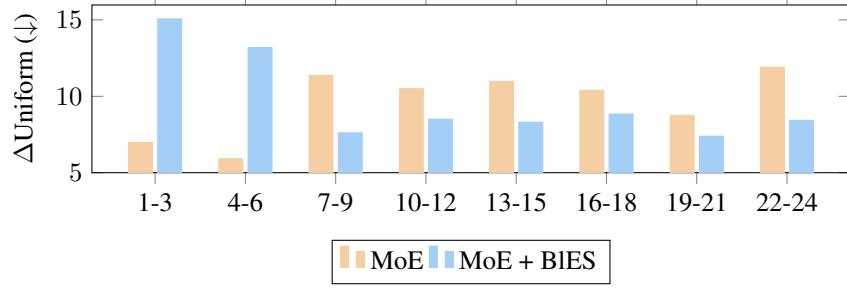
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<sup>4</sup>Please note that the shown inference latency improvement is batch-size dependent.

<sup>5</sup>Please note that our evaluations are executed in a server environment and actual on-device accelerator numbers might vary.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
$E_1$	1	0	0	0	0	0	0	0	0	1	1	1	0	0	0	1	1	1	1	1	0	0	0	1	0	0	0	0	0	1	1	0	0	0	
$E_2$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
$E_3$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
$E_4$	0	0	0	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
$E_5$	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
$E_6$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	
$E_7$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1	
$E_8$	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0		
$E_1$	0	1	1	1	1	1	1	1	1	0	1	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
$E_2$	1	0	1	1	1	1	1	1	0	0	0	1	1	1	1	1	1	1	0	1	0	0	0	1	1	1	1	0	1	1	1	1	1	1	
$E_3$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
$E_4$	1	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$E_5$	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
$E_6$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$E_7$	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$E_8$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

**Figure 5** Example expert replacements. 1 = Active Expert, 0 = Inactive Expert. Top: BIES, Bottom: MoE.



**Figure 6** Per layer analysis of the divergence of the expert routing from the uniform expert distribution. Large values indicate expert collapse and use of a pseudo-dense layer.

deeper architecture (see layer comparisons in Table 1). Looking at offloading enabled models, further slowdowns can be observed due to expert offloading delays. Comparing the standard offloaded MoE model against our BIES offloaded model, we find the 1.5x speed-up in generation speed, as previously presented in Table 3.

To put these results into context, inference-based offloading strategies, such as Eliseev and Mazur (2023) and Aminabadi et al. (2022) achieve a 2-3x and 5.5x generation latency reduction at the most comparable model size, which is still significantly larger than our on-device sized models. Furthermore, while orthogonal to our train-time improvements, inference-time offloading methods can oftentimes not be used in on-device centered scenarios, due to their additional modeling components required to predict future expert use.

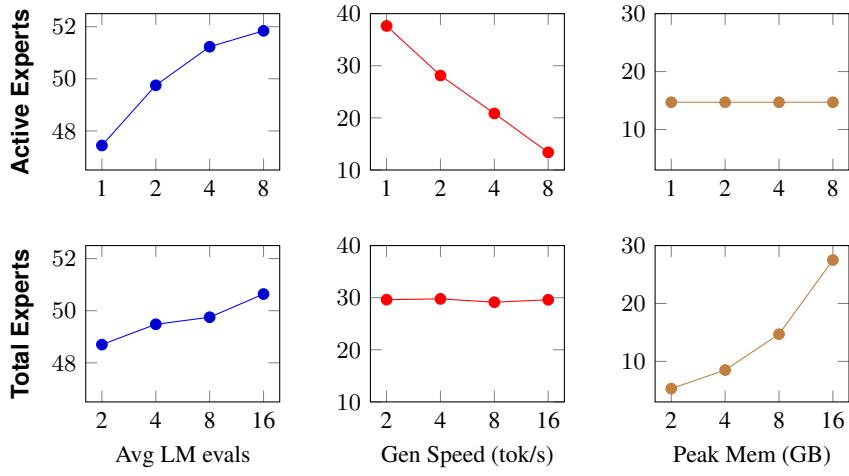
**Peak Memory:** We find that without expert offloading, the generation peak memory of the MoE model candidates is, as expected, comparable to the PA dense model. Using expert offloading, peak memory during generation is reduced to the FA dense model, given that only active parameters are kept in memory, making only offloaded MoE models true on-device candidates (see  in the right-most column).

### 3.4.4 On-Device Expert Ablations

In the previous sections, we followed the standard MoE setup with two active and eight total experts. Going beyond this popular MoE setup, we now ablate these dimensions and explore their impact on on-device model quality, latency and memory. Specifically, we’re exploring a suite of eight model ablations trained for 50,000 steps using a range of

Model	LM Eval	Latency		Mem	
Setup	Avg	Gen (tok/sec)		Gen	■
Metric	%	CPU	GPU	GB	✓ / ✗
Dense	48.78	4.47	73.10	5.8	✓
MoE	51.13	4.30	40.60	14.7	✗
+ WD	52.22	3.85	33.50	14.2	✗
+ Offl	51.13	4.30	15.02	5.4	✓
+ BIES	50.70	4.30	23.10	5.4	✓
Dense	52.80	1.77	42.60	14.0	✗

**Table 4** On-device benchmarks. Gen = Generation of 128 tokens (1 token prefill), Offl = Offloaded, BIES=Block-wise Expert Selection. Mem = Peak GPU memory. ■= Phone-sized, assuming <6GB of RAM use (e.g. iPhone 12 Pro).



**Figure 7** Active (top) and total (bottom) expert ablations of the 1.4B MoE model after 50,000 steps (~210B tokens)

active and total parameter counts. Figure 7 summarizes our findings along the active expert (left) and total expert (right) dimensions. For the active expert ablations, we fix the number of total experts to be 8, while the total expert ablations are fixed along the active parameter count (active experts=2).

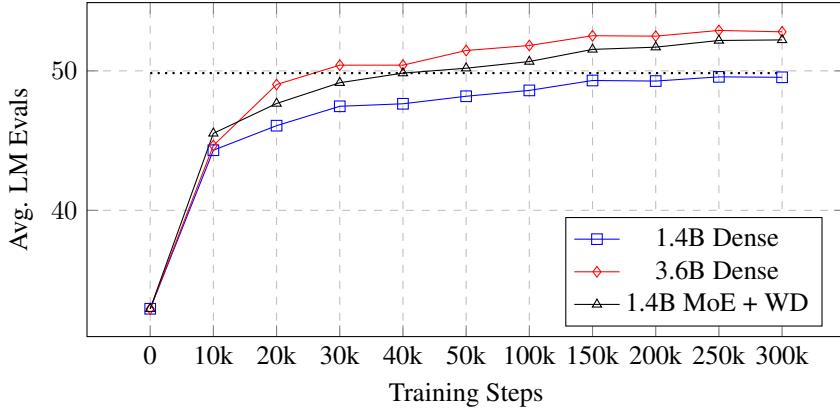
*Active Expert Ablation:* A larger number of active experts and, hence, a larger number of forward FLOPs improves model quality. However, approaching 8 active experts, returns are diminishing. Looking at the generation speed between settings, we find that the generation speed decreases linearly, while the peak memory is constant across increasing numbers of active experts<sup>6</sup>.

*Total Expert Ablation:* In this setup, model quality increases near linearly with the number of total experts. However, in comparison to the active parameter ablation, the quality improvement is less prominent (compare scales between sub-graphs). In regards of the generation speed and peak memory, increasing the total expert count does not impact generation speed, since the active experts and, hence, FLOPs are fixed. However, the number of total experts significantly impacts the peak memory consumption<sup>7</sup>.

To summarize, increasing the number of active and total experts improves model quality, however, requires a trade-off regarding either generation speed (i.e. latency) or memory.

<sup>6</sup>The peak memory would increase between settings if we actively offload experts.

<sup>7</sup>The peak memory would be constant if we actively offload experts, however, this would further impact the generation speed.



**Figure 8** Training dynamics across different model candidates

## 4 Training Efficiency

In Figure 8, we’re taking a look at the training process itself, comparing the training dynamic between MoE and dense model candidates, aligned by datasets, steps and hyper-parameters. Specifically, we compare the average language modeling performance between models at training checkpoints ranging from 10k to the full 310k steps.

Comparing the active parameter and total parameter aligned dense models with our best performing MoE model, we corroborate the findings in Lin et al. (2024), showing a 5-10x training efficiency gain using MoE models over their active parameter aligned dense candidates. Specifically, our MoE model candidate reaches the best performance of the 1.4B dense model at around 35k steps, while the larger and more powerful 3.6B dense model achieves generally higher scores.

## 5 Related Work

*Small Scale Language Models* With foundational models getting increasingly expensive to train and deploy, a dedicated effort has been made to develop small scale language models, aiming to enable foundational models to be deployed on-device (e.g. phones and glasses) or save compute during training and inference. Around those goals, two major research streams have formed:

(1) Improving small-scale foundational model architectures. For example, the MobileLLM paper Liu et al. (2024), proposes deeper, narrower models at the sub-1B scale to perform better than shallower and wider networks. Similarly Thawakar et al. (2024) propose MobiLlama, showing that both, training and deployment cost can be reduced when using carefully curated parameter sharing schemes. Lastly, the BabyLlama series Timiryasov and Tastet (2023); Tastet and Timiryasov (2024) shows that distilling knowledge from multiple teacher models leads to performance improvements under data-constrained conditions.

(2) Improving the training data. Previous work along this line explicitly aims to improve model performance through cleaner, more streamlined data. For example, the Microsoft Phi series Abdin et al. (2024) shows that using curated textbook data for small language model pre-training can significantly improve model performance. Furthermore, Huggingface showed that highly curated, education-style data can greatly support the language modeling task for small language models in their SMoLLM Ben Allal et al. (2024) and fine-web Lozhkov et al. (2024) efforts.

For a more in-depth comparison of small language models, we refer readers to Nguyen et al. (2024).

*Sparse Mixture of Experts* Mixture of Experts (MoEs) and, specifically, sparse Mixture of Experts have been exhaustively explored across different model sizes, including Qwen (2023; 2024) and OLMoE (2024) at the 1-3B active parameter scale, around 7B active parameters in the Mixtral (2024) and Deepseek (2024) models, all the way up to DBRX Databricks (2023) counting 36B and Grok-1 x.ai (2023) with 86B active parameter. Exploring training and inference trends, as well as major design decisions, the OLMoE paper Muennighoff et al. (2024) presents an important

milestone in the development of MoE models, specifically at smaller scales. Here, we follow many of the OLMoE findings in our model selection and definition. Specifically comparing the inner workings of large MoE models in regards to the role of different experts, Lo et al. (2024) compare Mixtral Jiang et al. (2024), Grok x.ai (2023) and DeepSeek DeepSeek-AI (2024) models, resulting in initial differences being found between model architectures, despite their different training paradigms. Here, we aim to make similar comparisons, however, focus on fairness between models, removing as many confounding factors as possible during our model comparison. For a more detailed exploration of previous MoE settings, we refer readers to Cai et al. (2024).

*Weight Decomposition for Mixture of Experts* As one of our extensions in this work, we propose a weight-decomposed version of a sparse mixture of expert model. Along similar lines, Dou et al. (2024) previously proposed a low ranking (LoRa) style extension of dense networks, effectively turning them into a mixture of expert model during the supervised fine-tuning (SFT) stage. By freezing the dense backbone model and using a router in the SFT stage, the authors argue that the final model is more robust against catastrophic forgetting of the pre-training knowledge. In comparison to their approach, we apply the weight-decomposition in the pre-training stage, directly training the backbone model using more parameter-efficient experts.

*Inference Efficiency* Lastly, we explore more efficient MoE parameter offloading through the use of our novel BIES loss term, closely related to previous work to enhance model offloading during model inference. Specifically, Xue et al. (2024) present “MoE-Infinity”, improving model expert pre-fetching and expert caching to reduce the number of model parameter transfers to and from the GPU. Similarly, EdgeMoE Yi et al. (2023) presents an inference framework to enhance MoE offloading latency through predictive offloading and bitwidth adaptations. Furthermore, other inference optimization frameworks exist, such as Mixtral Fast Inference Eliseev and Mazur (2023) and DeepSpeed Efficient Inference Aminabadi et al. (2022). Compared to this line of previous work, our approach is orthogonal, reducing the number of offloading actions during the model training stage, rather than at inference time.

## 6 Conclusion

In this work, we show how to enable sparse MoE architectures for on-device inference use-cases along the three on-device dimensions: Quality, Memory and Latency. Specifically, we show that in a fair comparison, MoE-style models outperform their dense counterparts on language modeling tasks by over +2.35%. Introducing our novel weight-decomposed experts, we show further performance gains of up to +1.1% compared to standard MoE models. To truly enable MoE-style models for on-device use-cases, we tackle the model offloading bottleneck by reducing expert offloads in the training stage and, in turn, reduce model inference latency. Our “grouped expert selection” loss term thereby improves expert offloading efficiency by 6x and increases generation speed by 50% compared to standard offloaded MoE models.

With the results presented in this paper, we effectively pave the way to unlock the potential of MoE-style architectures in on-device scenarios, supporting high quality, privacy preserving foundational models for edge devices.

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